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Sustainability metrics for rapid manufacturing of the sand casting moulds: A multi-criteria decision-making algorithm-based approach

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A R T I C L E I N F O

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A B S T R A C T

Additive Manufacturing has significantly developed over the years and is widely used in most industrial applications. Rapid Tooling refers to manufacturing the tools (moulds and dies) using Additive Manufacturing techniques. An essential application of Rapid Tooling is the 3D printing of sand moulds for castings. Metal casting is an energy-intensive process; and a lot of research has gone into the sustainability assessment of traditional sand castings. In this work, a robust decision-making approach is developed and implemented for sand mould manufacturing. Sustainability metrics for the mould production are formulated, and the conventional sand moulds are compared against the 3D printed sand moulds. A Multi-Criteria decision-making algorithm is implemented, and the effect of the batch size in the mould manufacturing is also studied. The discussed approach can help decision-makers choose the best mould manufacturing technique for the intended number of moulds to be manufactured.

1. Introduction

Additive Manufacturing (AM), also popularly known as 3D printing as per the NF ISO/ASTM 52900 standard, can be defined as; *"the process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies"*. AM technology was invented by Charles Hull in the year 1986. Hull's manufacturing method was termed stereolithography (STL) (Salonitis (2014)). In the early days, the architects used the technique to fabricate prototypes as the manufacturing process was fast and economical to use. It reduced the extra costs encountered in the manufacturing phase of an item. Lately, the AM methods transformed from producing prototypes to a fully functional product. The technology has significantly grown over the years and finds its application in Aerospace, medical, transportation, consumer products, etc. (Jiang et al. (2020)). The advantages of the AM includes: (1) Flexibility with the design constraints (Jiang (2020)), (2) Ease in manufacturing of complex shapes (Jiang and Ma (2020)), (3) Faster build speed/lower lead times (Gill and Kaplas (2009)), (4) Relatively inexpensive (Munish (2011)), (5) Accuracy in part production (Umaras and Tsuzuki (2017)), (6) Supports a wide variety of materials (Bourell et al. (2017)), (7) Ease in repair (Sauerwein et al. (2019)), and (8) Supports sustainable production (cleaner and produces less waste) (Chen et al. (2015)). Although AM offers several advantages, there are certain limitations associated with the process. The process is limited by (1) Surface quality (Delfs et al. (2016)), (2) Appropriate material selection (Bourell et al. (2017)), (3) High thermal stresses (Mun et al. (2015)), (4) High porosity in the parts/low density (Gorji et al. (2020)), (5) Suitability for manufacturing smaller parts (Bert Huis in 't Veld et al. (2015)), (6) Suitability for the low production volumes (Prakash et al. (2018)), and (7) Most AM techniques need supports (Jiang et al. (2018)).

Rapid tooling (RT) refers to the fabrication of tools with the help of AM techniques. It provides a solid capacity to adapt more efficiently to the changing consumer demands, providing a new competitive advantage. RT aims not to produce the final component but only to provide tools for the last component manufacture. With the use of RT, mass-production of moulds, dies, etc., can be done with many conveniences and ease (Karapatis et al. (1998)). Almost sixty AM methods are available today, manufacturing components in more than seventy different materials, including metals (Saxena et al. (2020a)), polymers (Saxena et al. (2020b)), and ceramics (Grimm (2006)). RT techniques can be classified into Direct and Indirect tooling techniques. When the manufactured components can directly be used as patterns for sand casting or as consumable patterns for investment casting, depending on the material, the process is termed as Direct tooling (Cheah et al. (2005)). Secondary methods may be used to transform the pattern (master) into

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the mould, thereby creating indirect tooling, which can further be used in other casting processes (Tromans (2004)).

Metal casting is characterised as an 'energy-intensive process'; because of the large energy consumption required for manufacturing one item (Pagone et al. (2018)). A report from the International Energy Agency (IEA) revealed that the industrial sector in 2016 was responsible for contributing 36% of the global CO_2 emissions (International Energy Agency (IEA) (2018)). The European Union (EU) has previously imposed stringent legislation related to emissions and climate control (Salonitis and Ball (2013)). In 2005, Emission Trading System (ETS) was established to focus on bringing down CO_2, NO_x and other carbon emissions, and between 2013 and 2016, a significant drop of 8% in the emissions was reported in the EU (Commission (2016)). Establishing such policies within the EU further promotes offshoring of manufacturing industries to the countries with relaxed norms. Thus, sustainability needs to be addressed for an energy-intensive process, and robust manufacturing approaches should be identified from a cleaner production perspective.

For these reasons, the AM capabilities are utilised to produce rapid moulds for sand casting (Sivarupan et al. (2021)). In the last two decades, a lot of research has gone into identifying and implementing the Binder Jetting (BJ) 3D printing method for producing the sand moulds (Upadhyay et al. (2017)). The permeability properties (due to the porous nature of the 3D printed mould) impose challenges as the mechanical properties of the conventional sand mould on the mechanical characterisation are difficult to produce with high precision. An investigation of the 3D printed sand moulds' mechanical characterisation is discussed by Dana and El Mansori (2020). The print orientation, together with the amount of binder and curing process parameters, also play a significant role in determining the mechanical properties of the 3D printed sand moulds (Sivarupan et al. (2020)). Such moulds' transport properties can be predicted using Non-destructive 3D characterisation techniques such as micro-X-ray Computed Tomography (Mitra et al. (2020)).

In the BJ-AM technique, a binder is used to selectively bond the sand granules (powder) in a layer by layer manner. The said technique can fabricate both the cores and the moulds. However, in most cases, a separate core is not required as the core design can be incorporated in the mould itself. This is in complete contrast to the conventional sand moulds, where to produce a hollow shape using sand casting, a core is required. The core is positioned inside the mould cavity allowing it to cast an internal feature. A skilled man is responsible for manufacturing the cores, and thus precision and accuracy of the part are highly dependent on the artisans (Chua et al. (1998)). The moulds utilised for the sand casting are expendable, meaning one mould can only be used one time for producing a part. Thus for the large production volumes, the conventional mould manufacturing process is time-consuming and labour intensive. Furthermore, to obtain repeatability in castings, precision manufacturing of the mould is desirable.

In their recent paper, Sama et al. (2020) identified and discussed the approach for integrating AM in the foundries. The authors presented various case studies to validate the potential of 3D printed sand moulds. Difficult-to-machine castings are represented with a case of a closed vane impeller. The design complexity of the impeller further imposes challenges in the mould fabrication through conventional mould manufacturing strategy. In another case study (discussed in the same work) of a complex bracket with many undercuts and smaller features was manufactured using RT, which otherwise are very difficult to manufacture using conventional tooling. The authors fabricated multiple brackets by placing them adjacent to each other thereby facilitating the production of multiple components in one go. Through the validations, the authors claim that the AM of sand moulds is a soft tooling solution to lower down the shrinkage in the castings, the lead time can be reduced to a larger extent, multiple parts can be produced in a single AM operation, complex castings can be produced with ease without the need of core. The hybrid manufacturing method further has the potential to transform the future of the foundries.

Multiple ways of improving the performance of AM sand moulds with the hollow structures are discussed by Deng et al. (2018). The effect of heat flux was modelled and simulated using COMSOL. The authors concluded that better insulation could be achieved by incorporating various design alterations in the 3D printed sand moulds. Snelling et al. (2015) discussed the manufacturing of lightweight cellular structures using 3D printed sand moulds. These structures are known to possess good strength, better stiffness, high thermal insulating properties, high stiffness, etc. However, in the manufacturing of such components, the challenge lies in the joining process. Typically the joints are either bolted or welded, thereby producing enormous stress. This limitation is overcome by 3D printed sand moulds which, allow pattern-less casting. The authors also discussed the FEM model and concluded that such structures could absorb larger impact forces than the solid structures produced by the same material of the same weight. Almaghariz et al. (2016) presented a cost vs complexity function in a comparative study of the two tooling techniques. The authors estimated the overall fabrication costs as a function of the number of cores constrained by the part's geometry. For low production volumes, the AM based tooling technique was found to be economical. The inference was based on the two case studies discussed in their work but lacked a robust assessment method applied to any other case.

As it is evident from the literature, most of the research in this domain is limited to the process optimisation (Papanikolaou and Saxena (2021)), design improvements in the 3D printed sand moulds (Deng et al. (2018)), and mechanical testing of the sand moulds (Kridli et al. (2010)). There exists a research gap deploying a suitable decision-making approach to identify the scenarios in which one tooling technique is advantageous over the other, especially from a sustainability perspective. In one of the recent works by Pagone et al. (2021), the authors, for the first time, introduced the sustainability metrics for 3D printed sand moulds. The approach in the previous work was limited only to establishing the metrics for producing one mould component using conventional and AM based tooling techniques. For low production volumes, the AM based tooling technique was found to be advantageous over its traditional counterpart. The current paper discusses even more complex scenarios.

A small number of works in the scientific literature examine the sustainability of the AM sand moulds, considering the resource-intensive nature that characterises metal casting. When discussing sustainability, energy efficiency, which is environmental sustainability indicator is more prevalent while determining the sustainability of metal castings. Carabalí et al. (2018) published an overview of Colombian metal casting plants establishing virtuous energy efficiency technological strategies. Sa et al. (2015) established the connection between management strategies and the analysis of energy efficiency in a Swedish foundry In many geographical areas, such as Europe (Trianni et al. (2013)), Sweden (Rohdin et al. (2007)) and Italy (Cagno et al. (2015)), barriers to energy production in foundries have been empirically studied. While these findings are helpful, it has been seen in the literature that if considered without including other product life phases outside production, the effect of energy efficiency or sustainability measures may be very minimal or misleading.

The work presented in this paper focuses on establishing a robust decision-making framework for the tooling process selection for casting. The conventional tool manufacturing method is compared to rapid tool manufacturing. Integration of the AM for 3D printing of sand moulds is relatively economical and less time-consuming. A novel method for carrying out this form of research with a simple and comprehensive process for measuring the indicators' values is proposed. Besides, such a framework instantly generates a high-resolution map of decision-making space with objective weighting dependent on the ordinal, combinatorial ranking of the parameters. This function eliminates significant deficiencies in sustainable Multi-Criteria Decision Analysis (MCDA) manufacturing: the considerable amount of feedback needed by experts or DMs, the possible inconsistencies that could exist between them, and the limited reach of pre-determined, arbitrary samples of the decision-making space. The discussed approach is applied for the manufacturing of sand moulds in four different batch sizes. The presented approach does not involve any specific assumptions in the mould fabrication for metal casting, and thus, it can be applied to assess the sustainability of any production method.

2. Multi-criteria decision-making for sustainability in castings

Haraldsson and Johansson (2018) explored energy efficiency prospects in aluminium-based metal manufacturing-related processes ranging from pre-production to recycling. The authors found that certain production processes are less energy-intensive than electrolysis of raw materials. Energy savings can also be accomplished by creating new materials and integrating manufacturing processes that minimise demand during the product period of use (instead of production), as seen by the combination of casting and forging processes by Krüger et al. (2019). An LCA is discussed by Salonitis et al. (2019) when introducing a new casting method designed to improve energy efficiency and consistency. Mittal et al. (2020) recently presented a neural network-based approach when discussing the decision-making algorithms for suitable process selection to optimise energy conversion efficiency from raw materials such as coal.

MCDA techniques such as Analytic Hierarchy Process (AHP) has previously been applied in the literature for decision-making in the manufacturing processes. Multi-Objective Decision Analysis (MODA), a type of MCDA where discrete possibilities are replaced by continuous variables representing process parameters, was used in a complete factorial analysis to optimise Electro-Discharge Machining (EDM) practices, taking into account five DM and their sensitivities (Dewangan et al. (2015)). However, in this analysis, no LCA factors are assessed, leaving a research gap (Filipič et al., 2015). For the early stages of product design, Favi et al. (2016) merged a MODA technique with MCDA to choose the best alternatives based on the five defining attributes (i.e. assembly, cost, materials, time and production method) and explained the approach with a case study. With a discrete rating scale, the authors used the MCDA Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to point out that a sensitivity analysis is essential to enable the subjectivity of values and weights taken into account. This typical shortcoming is discussed in an original way by the ordinary combinatorial rating of parameters provided in this article. In the scientific literature, findings on MCDA related to metal casting (without explicitly addressing sustainability issues) are minimal.

Neto et al. (2008) proposed a framework for determining the critical causes of emissions during the process phase of the aluminium die casting plant manufacturing car parts. Their method merged LCA, environmental management systems and an MCDA algorithm with four distinct weighting distributions. Although the chosen weight distributions provided some information, such an approach failed to provide a holistic image of the decision-making region, extracting some randomly placed, isolated samples.

Based on the five parameters (cost, tardiness, cooperation, flexibility and quality), Chakraborty et al. (2005) applied AHP to decrease the number of die casting vendors in a regional location in India. In another work, Singh et al. (2006) merged the lean methods (Value Stream Mapping), fuzzy logic and MCDA to define waste (according to the lean thought principle) using a Multi-Attribute Utility Function (MAUF) and to consider several DMs for a die casting factory (pressure and gravity die casting processes). Pal and Ravi (2007) combined Quality Method Implementation (QFD) with Analytic Network Process (ANP) techniques to pick the best process for manufacturing sand and investment casting patterns, based on the casting engineer's criteria and a database, among twenty alternatives. The combination of the QFD-ANP approach is utilised to measure the tooling attributes' weights by pair-wise comparisons. This is a very daunting and time-consuming task. For a few MCDA strategies (such as AHP and ANP), which are indeed very time-taking, the proposed automated mapping solution can be applied with ease.

The latest MCDA frameworks, primarily built for sustainable production, answer the lack of quantitative studies in the sustainability literature (Stoycheva et al. (2018)). The approach suggested by the authors centred on the broad range of sustainability in the automobile industry and demonstrated the preference of five alternate materials and 15 parameters based on the three pillars of sustainability (Saxena et al. (2020c)) by using the Weighted Sum Method (WSM) and the Sensitivity Analysis. Pagone et al. (2020) introduced a novel, objective MCDA methodology able to describe the decision-making space in detail using an automatic, ordinal combinatorial weighting technique with metrics categorisation. The methodology is illustrated with a case study on the material selection for High-Pressure Die-Cast (HPDC) automotive parts using TOPSIS and including product LCA considerations (Pagone et al. (2020)). The same methodology has also been applied to the MCDA of Wire Arc Additive Manufacturing (WAAM) competitiveness against conventional processes of three different materials typical of aerospace and infrastructural products (Priarone et al. (2020)).

From the discussed state of the art, it is evident that there is minimal work that is focused on the integration of sustainable metal casting by utilising MCDA techniques. No previous work is carried out which focuses on the manufacturing process selection for mould fabrication in metal casting simultaneously, including LCA considerations. The MCDA approach applied in this work is based on the techniques discussed by the authors in their recent work (Pagone et al. (2020)).

3. Tooling for sand casting

3.1. The sand casting process

Shape casting is a manufacturing process suitable for producing complex geometries in metal and alloy with high melting points without limitation on their size. In a conventional shape casting process, a mould is first fabricated. The process makes use of expendable moulds, which are only used once and destroyed after. Thus, the process imposes specific challenges on the mass production of parts. In this process, a hollow sand mould is fabricated so that the mould's internal geometry is a replica of the final casting desired to be manufactured. The molten metal is poured inside the mould cavity and left to cool down. The molten part solidifies at room temperature, and the shape of the mould is mirrored onto the solidified metal. The part thus obtained is referred to as Casting. The process finds its use in fabricating near-net-shape geometries. In sand casting, the mould is prepared using foundry sand. Due to the insulating properties of the sand mould, the molten metal usually experiences a lower cooling rate, and thus the process is particularly advantageous for manufacturing complex geometries from hard-to-machine materials (DeGarmo et al. (2003)).

In an application such as engine blocks, where an intricate internal shape is desirable, a secondary element called core is used inside the sand mould. The cores are prepared using silica sand mixed with a binder and cured afterwards. Sometimes, the core is also further coated and baked before use. The molten metal accumulates between the spacing formulated by the core and the internal boundary of the sand mould. This allows both internal and external features of the casting to be conveniently fabricated. After the molten metal is solidified, the mould is broken, and the casting is removed. Sometimes, an additional heat treatment step is carried out on the casting to improve the material properties.

The disposal of sand casting waste is one of the primary environmental concern for the foundries. The used moulding sand is disposed of as landfill in the environment. These sands produce dust containing the binder remains. Typically, for every two tons of casting, one ton of sand is disposed to landfills, which creates a negative environmental impact. With the integration of AM in the conventional mould making process, around 60% of the resources (sand) can be saved, thereby reducing the environmental impact (Sivarupan et al. (2021)). The AM process consumes only a small percentage of the energy spent on manufacturing the final product. Ignoring the CO_2 emissions involved in the production of the 3D printers, one can safely argue that the mould printing process, when coupled with the renewable energy sources for operating the 3D printers, can lead to a cleaner environment.

The subsequent sections will focus on a comparative assessment for establishing sustainability metrics for sand mould manufacturing.

3.2. Conventional tooling

To manufacture a conventional sand mould, a 'pattern' is needed. The pattern is a negative replica of the final product and is made in either metal, wood or plastic. The pattern is made slightly larger in dimensions than the desired product to account for the 'contraction allowance'. To accommodate single or multiple cores at a later stage, 'core prints' are embedded within the pattern. A runner, sprue and gate arrangement is made on the pattern to facilitate the molten metal flow. Another key component is the casting flask, divided into two halves known as cope and drag. The pattern is then made to fit inside the casting flask. The sand is squeezed and rammed around the pattern to fill in the spaces between the pattern and the casting flask. Additional components such as chills are sometimes added to promote directional solidification.

Conventional tooling involves the manufacturing of sand moulds using green sand. The green sand is a mixture of Silica sand, Zircon sand, Chromite sand, bentonite, water, inert sludge and anthracite in varying proportions. The type of sand depends on the pouring temperature of the molten metal. There are several methods of packing the sand around the pattern. In this work, it is considered that the sand is pneumatically packed. A hydraulic powered system is used to compact the sand in the flask. From the energy perspective, the energy consumed in compacting the sand is used.

The energy consumption in mould and core manufacturing can be quantified in terms of Specific Energy Consumption (SEC_m - mould) and (SEC_c - core), respectively. The values of SEC_m and SEC_c in a conventional sand casting process are reported to be 0.16 MJ/kg and 0.51 MJ/kg respectively (EduPack (2016)). The total energy consumption (E_c), (in MJ) can thus be calculated from equation (1).

$$E_c = (SEC_m * w_m) + (SEC_c * w_c) \tag{1}$$

where w_m and w_c are the weight of the sand used for manufacturing the mould and core respectively. Utilising the values of E_c obtained from equation (1), carbon emissions $CO_{2,c}$ in $kgCO_2$ can further be evaluated from equation (2). The carbon intensity for generating the power using grid electricity is assumed to be 325 g CO_2/kWh. The real-time data for carbon intensity can be obtained from ICAX, and can be substituted in the numerator of equation (2).

$$CO_{2,c} = \left(\frac{325}{3,600}\right) * E_c \tag{2}$$

These equations can be used to estimate the environmental sustainability (in terms of energy consumption and carbon footprint) for conventional sand mould manufacturing.

3.3. Rapid tooling

As discussed in the earlier sections, AM techniques can be utilised for producing direct tooling, indirect tooling, and patterns (or moulds) for sand castings (shown in Fig. 1). The term rapid tooling stands for the use of AM techniques for producing tools or moulds. Based on the physics of the process, seven classes of AM techniques can be identified, namely, (1) Material extrusion, (2) Powder Bed Fusion, (3) Material Jetting, (4) Binder Jetting, (5) Directed Energy deposition, (6) Sheet lamination and, (7) VAT photopolymerisation. The AM technique for producing sand moulds is Binder Jetting (BJ).

BJ, also commonly referred to as Three Dimensional Printing (3DP) process, was invented at the Massachusetts Institute of Technology (MIT). There are several types of binders commercially available that can be used for 3D printing of sand moulds. The most popular are the Furan binders which are furfuryl alcohol-based binders and chemically cured. Any remaining moisture can be removed at a later stage with or without additional heat treatment methods. Other binders include CHP binders which are alkaline phenolic resole (ester-cured), HHP binders (phenolic resole, acid cured) and water-based inorganic binders. All the other binders except the furan binders require post-curing (heat treatment) at higher temperatures. The sand that can be used in the AM process is Silica sand (SiO_2). This is the most economical and readily available material. The sand moulds fabricated from the silica sand possess low thermal conductivity. Another material alternative is a combination of Zirconia, Olivine, Chromite, Zircon and Chamotte. This combination is known to improve the thermal conductivity of the sand moulds and are comparatively more expensive.

The material processing is done in the following steps. At first, a CAD model of the part is prepared using standard CAD software. The CAD data is then fed into the BJ setup (3D printer). The first layer of sand is spread on the build platform using a re-coater. The binder droplets are then sprayed using an inkjet print head which can move in the x-y plane. The build platform is then lowered along the z-axis, and the process is repeated to form the next layer. The process is repeated till the desired part is produced. Once the process is finished, the part is removed, and the unbound sand is cleaned using pressurised air and a brush.

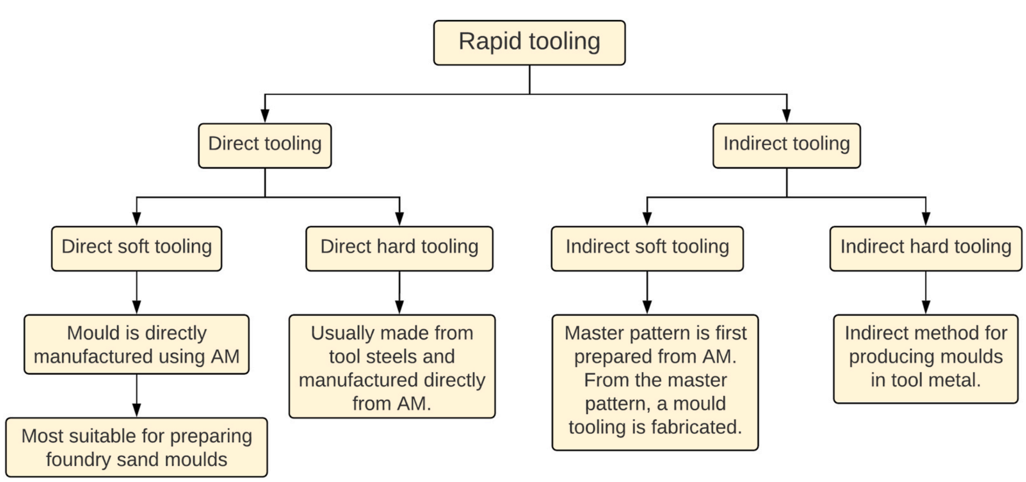

Fig. 1. Classification of rapid tooling.

3.3.1. Energy consumption

The quantification of energy consumed in producing rapid sand moulds is dependent on the type of 3D printer used. There are many commercial 3D printers available from 5,000 W to 10,300 W power consumption. In this work, the VX500 Voxeljet 3D printer is considered. The method can be adapted and applied to a different printer type. The maximum printer speed is $3*10^{-6}m^3/s$ with machine power equal to 10,300 W. The reason for such a printer's choice is to evaluate the maximum energy consumed for producing rapid sand moulds. If the density of the parts to be produced are 1,738 kg/m^3, then the Specific Energy Consumption ($SEC_{m,c}$ for printing mould and core with VX500 Voxeljet 3D printer is 1.08 MJ/kg (Sivarupan et al. (2019)). If the rapid sand moulds are utilised for energy-efficient sand casting operations, such as Constrained Rapid Induction Melting Single Shot Up-Casting (CRIMSON), this can bring down the overall energy consumption costs, thereby making the complete sand casting process even more sustainable (Papanikolaou et al. (2020)). The overall energy consumption (E_{3D}) - in MJ, can thus be evaluated from equation (3).

$$E_{3D} = SEC_{m,c}*(w_m + w_c) \tag{3}$$

Similar to the equation (2), carbon emissions for 3D printed moulds ($CO_{2,3D}$) - in $kgCO_2$ can be evaluated from equation (4).

$$CO_{2,3D} = \left(\frac{325}{3,600}\right)*E_{3D} \tag{4}$$

4. Metrics for tooling process selection

In this section, the effect of environmental sustainability, quality, cost and time in formulating a decision-making strategy for optimal manufacturing process selection is discussed. For each quantity, the positive or negative effect on the method of mould making is established. These metrics are shown in the Table 1. The choice of metrics is based on the suitability and ease of availability of the literature's data. The current analysis is also focused on understanding the variation in the metrics with the number of parts. This is important because the manufacturing cost of rapid tooling increases with an increase in the number of parts produced. The number of parts (henceforth referred to as batch sizes) are varied from a single mould (B1), five moulds (B5), ten moulds (B10), and fifty moulds (B50)

4.1. Environmental sustainability

Sand casting is one of the many production processes that involve high energy consumption. The total energy consumption in manufacturing a sand mould can be identified from equation (1) and equation (3). The high energy consumption generates significant CO_2 emissions which can be determined from equation (2) and equation (4). Hawaldar and Zhang (2018) manufactured a mould for fabricating a pump bowl. The material data from their work is utilised for calculations in this section. Both the core and the mould were printed using the VX500 3D printer. The total sand weight (w_m) in the conventional and 3D printing processes was reported to be 301 kg and 90 kg, respectively. Weight of sand utilised for manufacturing core (w_c) 7.7 kg (conventional) and 3.3 kg (3D printed). The overall weight of the two moulds (w_{cast}) produced from conventional and 3D printing were 34 kg and 23 kg, respectively.

From equations (1) and (3), the specific energy consumption for producing one mould is calculated as $E_c = 52.08$ MJ and $E_{3D} = 110.36$ MJ. Similarly from equation (2) and equation (4) the CO_2 consumption is evaluated as $CO_{2,c} = 4.70$ $kgCO_2$ and $CO_{2,3D} = 9.96$ $kgCO_2$.

For the manufacturing of multiple identical moulds, the weight of the sand utilised for manufacturing the core and the mould would be in proportion to the number of moulds produced. Thus, equations (1) and (3) can be modified into equations (5) and (6), where n is the number of moulds desired to be produced by the two manufacturing processes. The computed values are summarised in Table 2

$$E_c(n) = (SEC_m * w_m * n) + (SEC_c * w_c * n) \tag{5}$$

$$E_{3D}(n) = SEC_{m,c}*(w_m * n + w_c * n) \tag{6}$$

4.2. Cost

The cost is yet another significant decision-making factor. Cost involved in manufacturing moulds can be referred to as 'Tooling cost'. Tooling cost is a summation of material cost, labour cost, equipment cost, energy cost and manufacturing costs. Moulds produced by 3D printing can potentially save up to 75% of the tooling costs (Voxeljet (2019)). The costs are dependent on the number of parts required to be produced and the lead time of parts (t_{lead}) (Hawaldar and Zhang (2018)). The tooling costs for the conventional tooling and the rapid tooling are shown in the Table 3. The tooling time and tooling cost data are provided by the manufacturer of the 3D printer Voxeljet (2019).

4.3. Quality and mechanical properties

The quality metric is analysed in terms of the part quality fabricated from the conventional mould and the 3D printed mould. The material properties defining the quality of parts is adapted from Snelling et al. (2013). The strength of the mould is the most significant factor when considering the quality. The sand used for manufacturing a 3D printed part is the commercially available printing sand $ViriCast_{TM}$, procured from Viridis 3D. Strength is determined using tensile tests. Five specimens were 3D printed in a dog bone structure and cured at 204.4°C for 5 h. The strength is compared with the specimens manufactured using conventional no-bake foundry sand mould. The 3D sand mould permits the production of castings up to a maximum of 1,454.4°C. The mean tensile strength (σ_t) from the tests was evaluated to be 0.16 MPa (3D printed) and 0.56 MPa (conventional).

Another quality criterion is the average surface roughness (R_a) of the mould. The R_a values were reported to be 13.62 μm (3D printed) and 12.17 μm (conventional). No change in the part density was reported. Both processes produce the parts with the same density, so density is excluded from the current analysis.

Compared with those produced from no-bake moulds, castings

Table 1
Metrics for process selection.

Quantity	Impact	Category
Total sand used in mould manufacturing	Negative	Environmental sustainability
Total sand used in core manufacturing	Negative	
Weight of the casting	Negative	
CO_2 emissions	Negative	
Total energy consumption	Negative	
Hardness of casting	Positive	Quality
Surface roughness of casting	Negative	
Compressive strength of casting	Positive	
Porosity of casting	Negative	
Tensile strength of the mould	Positive	
Cost	Negative	Cost
Mould manufacturing time	Negative	Time

Table 2
Environmental sustainability metrics for sand mould manufacturing.

Batch size	Total energy consumption (MJ)		Carbon Intensity ($kgCO_2$)	
	E_c	E_{3D}	$CO_{2,c}$	$CO_{2,3D}$
B1	52.08	110.36	4.70	9.96
B5	260.43	551.81	23.51	49.81
B10	520.87	1103.63	47.02	99.63
B50	2604.35	5518.19	235.11	498.17

Table 3
Tooling cost for conventional and 3D printed parts (Voxeljet (2019)).

Batch size	Conventional tooling	Rapid tooling	
	t_{lead} = 4–6 weeks	t_{lead} = 5 days	t_{lead} = 21 days
B1	3,600	898	410
B5	3,684	3,080	1,428
B10	3,789	5,490	2,525
B50	4,628	22,275	10,300

manufactured from AM were more porous. In AM moulds and no-bake moulds, the average porosity was found to be 1.13% and 0.65%, respectively (Snelling et al. (2013)). The Vickers Hardness of the AM moulds was reported to be 92.7 HV, and for the no-bake mould, the hardness value was 82.1 HV. Compressive strength was also tested on the metal cylinders, and the observed values were 170.8 MPa (3D printed) and 165 MPa (no-bake mould). Since the quality metric is independent of the number of moulds produced. Metric values for all the batch sizes remain the same.

4.4. Time

Total time spent in manufacturing a sand mould is equal to the summation of the mould making time, core manufacturing time and fettling time. The 3D printing process is a pattern-less process; thus, for comparison, pattern manufacturing time is excluded from the conventional mould making process. The time spent dismantling the mould and removing the feeder head, and riser is referred to as the fettling time. Time spent on manufacturing one mould part is taken from Hawaldar and Zhang (2018). The time spent is directly proportional to the number of parts produced both from the conventional tooling and the rapid tooling. However, it is possible to fabricate multiple parts together in the rapid tooling but for the current analysis, the time spent is calculated by numerically multiplying the batch size with the time spent for manufacturing one single mould. The computed values are shown in the Table 4.

4.5. Multiple criteria decision analysis high resolution mapping methodology

To develop a robust decision-making strategy, the TOPSIS-MCDA algorithm is implemented. The algorithm is based on identifying the best solution from the available alternatives. Such a solution is closest to the positive ideal solution (A^+) and farthest from the negative ideal solution (A^-). Fig. 2 shows the sequence of steps of the implemented TOPSIS algorithm.

For 'm' number of alternatives and 'n' decision criteria values, a decision matrix X can be represented as:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,n} \\ x_{2,1} & x_{2,2} & \dots & x_{2,n} \\ \vdots & \vdots & \dots & \vdots \\ x_{m,1} & x_{m,2} & \dots & x_{m,n} \end{bmatrix} \quad (7)$$

Each of the decision-criterion in the matrix X is then normalised using equation 8

Table 4
Time metric for conventional and 3D printed mould parts (Hawaldar and Zhang (2018)).

Batch size	Mould manufacturing time - in min	Mould manufacturing time - in min
	(Conventional tooling)	(Rapid tooling)
B1	300	45
B5	1,500	225
B10	3,000	450
B50	15,000	2,250

$$r_{i,j} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{k,j}^2}} \quad \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \quad (8)$$

For every criterion within the matrix, its importance can be defined using a vector 'n' with weights 'w', such as $\sum_{j=1}^{n} w_j = 1$. The normalised weighted matrix V can then be written as (equation (9))

$$v_{i,j} = r_{i,j} W_j \; \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \quad (9)$$

The positive ideal solution (A^+) and the negative ideal solution (A^-) are then computed using the maximum and the minimum values of equation (9). For each criteria, one of the following two conditions are computed:

- If the criteria has an overall positive impact then, $Max(A^+)$ and $Min(A^-)$ are evaluated.
- If the criteria has an overall negative impact then, $Min(A^+)$ and $Max(A^-)$ are evaluated.

The distance (d_i) of each given alternative from A^+ and A^- can be evaluated from equation (10) and equation (11) respectively.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \; \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \quad (10)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \; \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \quad (11)$$

The last step is to compute the relative closeness to the negative ideal solution using equation 12

$$s_i^- = \frac{d_i^-}{d_i^+ + d_i^-} \; \forall i \in \mathbb{N} \cap [1,m] \quad (12)$$

This further ranks all the alternatives and the highest s_i^- gives the best solution.

4.5.1. The automated weight distribution

In the present analysis, four weighting distributions are used to describe the decision-making space exhaustively. Namely, the four weight distributions have been called "uniform", "halving", "quadratic" and "first two" (Fig. 3), and they are expected to cover the vast majority of possible DMs' point of view. Such an approach has been introduced in authors' previous work (Pagone et al. (2020)). For the uniform weight distribution, each criterion is assigned equal weight; i.e. every criterion is treated as of equal importance. For all the other weight distribution, the weight w is decreased by a factor $f_w(j)$ at each successive j-th place in the ranking as seen from the equation (13).

$$w(j) = \frac{1}{f_w(j)} \; \forall j \in \mathbb{N} \cap [1,n] \quad (13)$$

For halving weight distribution, $f_w(j)$ is computed using equation 14

$$f_w(1) = 1 f_w(j) = 2 f_w(j-1) \; \forall j \in \mathbb{N} \cap [2,n] \quad (14)$$

For quadratic weight distribution, fw(j) is computed using equation 15

$$f_w(j) = 2j^2 \; \forall j \in \mathbb{N} \cap [2,n] \quad (15)$$

For first two weight distribution, fw(j) is computed using equation 16

$$f_w(1) = f_w(2) = 1 f_w(j) = j^2 \; \forall j \in \mathbb{N} \cap [3,n] \quad (16)$$

In addition, an extra weighting dependent on the entropy of information contained in the values of parameters is added. The importance of using entropic weights is that it is another objective method of setting weights without the decision maker's intervention. The value of parameters for a greater degree of divergence is intensified and thus more

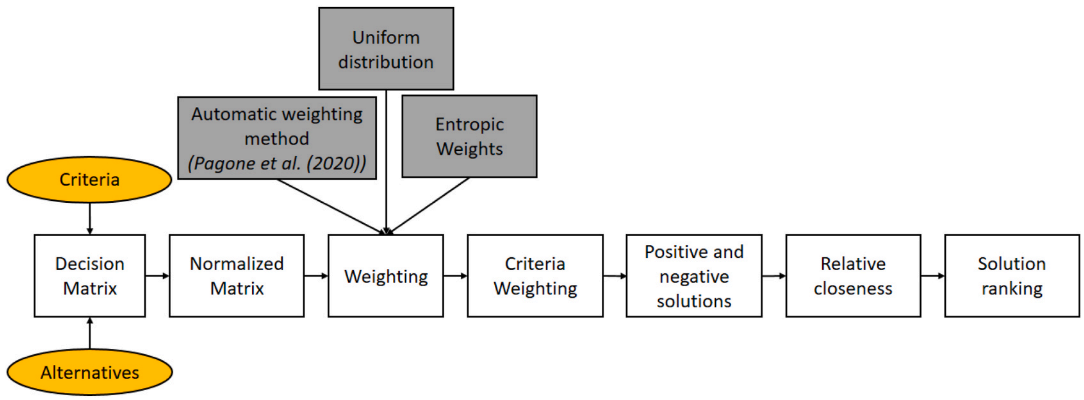

Fig. 2. Flow chart showing the implemented MCDA approach. Based on the authors' previous publication (Pagone et al. (2020)).

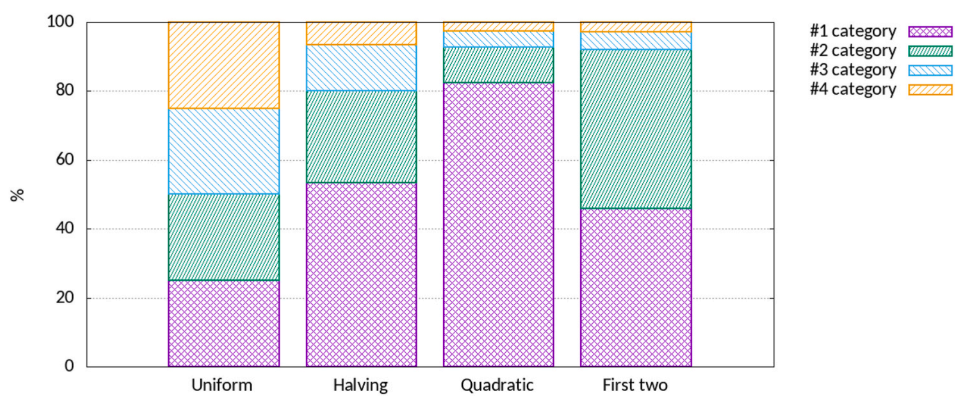

Fig. 3. Weight distribution laws used in the present analysis. Image adapted from Pagone et al. (2020).

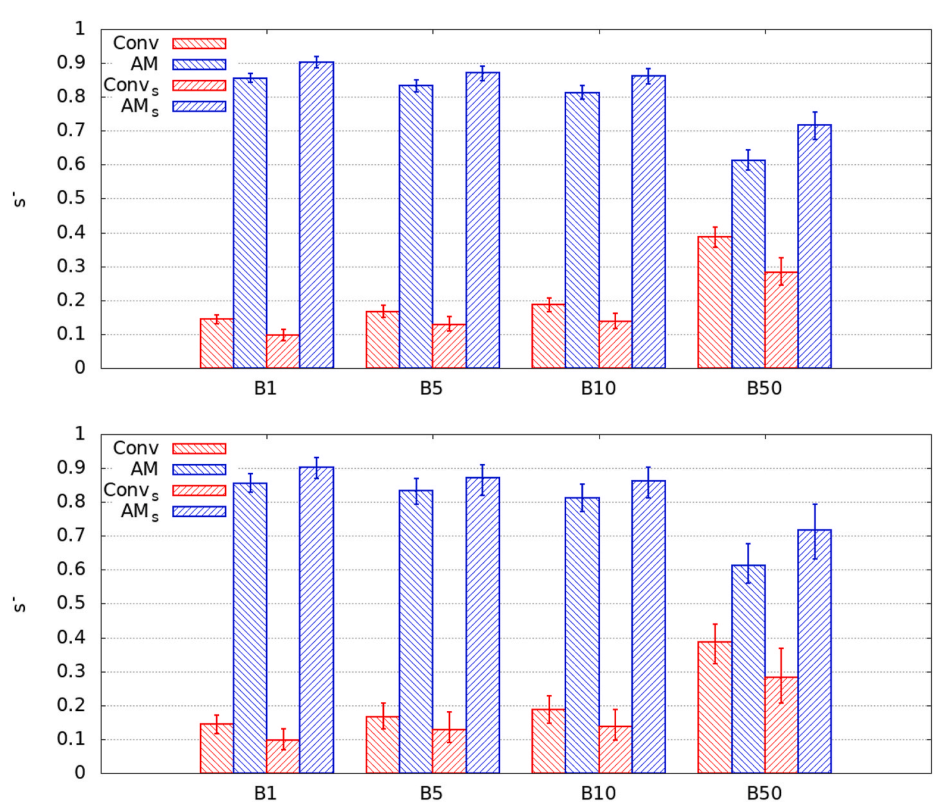

Fig. 4. Final multi-criteria score s^{-} of alternatives (i.e. conventional and additive manufacturing) with equal importance of categories (called "uniform" weight distribution) and 5% (top) and 10% (bottom) uncertainty.

specifically differentiated. The estimation of entropy E for n-criteria of the decision matrix R is done from equation 17

$$E_i = -\frac{1}{ln(n)}\sum_{i=1}^{n} r_{ij}ln(r_{ij})\ \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \tag{17}$$

The entropic weighting (w_i) is calculated by combining the weights calculated by the four distributions (w_d) discussed above, using equations (18) and (19)

$$w_{s,i} = \frac{|1-E_i|}{\sum_{i=1}^{n}|1-E_i|}\ \forall i \in \mathbb{N} \cap [1,n] \tag{18}$$

$$w_i = \frac{w_{s,i}w_{d,i}}{\sum_{i=1}^{n} w_{s,i}w_{d,i}}\ \forall i \in \mathbb{N} \cap [1,n] \tag{19}$$

5. Results and discussion

When the four categories considered are equally important for the decision-maker, a 5% and 10% uncertainty in the values of criteria is considered for different batch sizes (Fig. 4). It is apparent from these results that, although the AM of moulds is overall preferable to the conventional, with the increase of the batch sizes, such advantage reduces. However, even with the maximum size of 50 parts per batch, the additive process is still more beneficial, notwithstanding a higher uncertainty (i.e. 10%) in the criteria or entropy weighting or both the effects combined.

Furthermore, when different category weight distributions are considered (as presented in Section 4.5), only a 5% uncertainty range will be represented because (as illustrated in Fig. 4) it does not affect the conclusions significantly, and it reduces the readability of the maps. Parts of the map background have the same colour as the best alternative. As a general statement, simple considerations cannot be made because the decision making space is rather complex.

For single-part production, it appears that AM is generally the best option regardless of specific weight distribution laws (Fig. 5). The only exceptions occur when quality is very important, i.e. in cases starting with "q" with the "quadratic" law or in one of the first two positions in the "first two" map. Such exceptions can be subdivided into cases when.

- conventional manufacturing is clearly better, i.e. when time and cost are not important ("qetc" and "qect" "quadratic" law cases);
- there is substantial uncertainty, i.e. when environmental sustainability has some level of importance in combination with the mentioned strong relevance of quality ("qtec", "qtce", "qcet" and

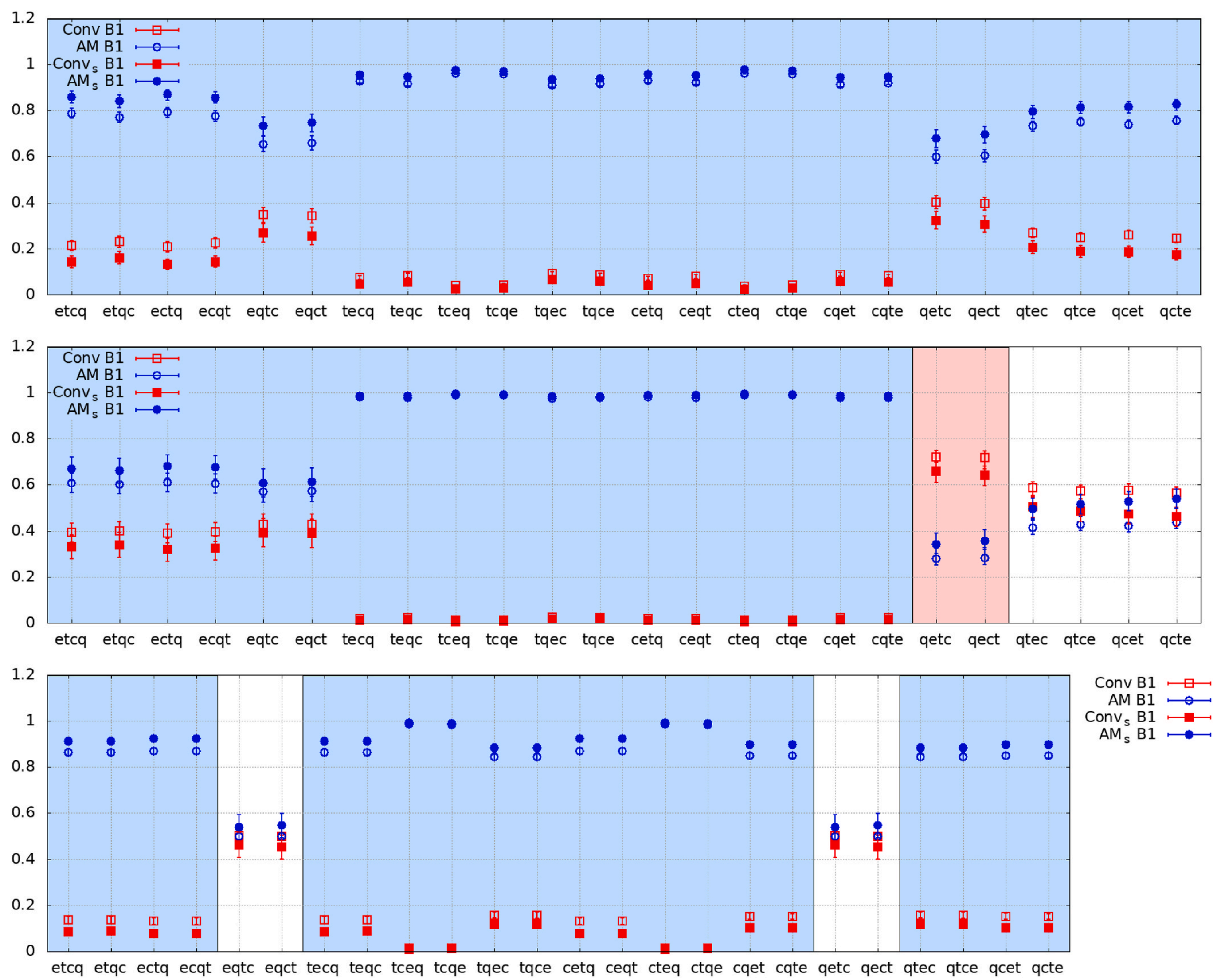

Fig. 5. Decision making maps showing the final score s^{-} of alternatives for single piece batch size (B1) of the "halving" (top), "quadratic" (middle) and "first two" (bottom) weight distribution laws and 5% uncertainty of criteria values. The background colour indicates that the alternative with the corresponding data points is better, whereas no colour means uncertainty.

"qcte" with "quadratic" law and the "symmetric" conditions with "first two" "eqtc", "eqct" and "qetc", "qect").

Analysing further the uncertain cases, it can be seen that the "quadratic" distribution law shows rank reversals determined by the introduction of entropy weighting ($Conv_s$ and AM_s points on the maps).

If larger batch sizes are considered, while many fundamental trends stand, conventional mould making appears the preferred process more and more often. With batches of five pieces, the map corresponding to the "halving" weight distribution law shows again a strong dominance of the AM over conventional manufacturing (Fig. 6). There is only one exception for the "qect" case, where there is substantial uncertainty not entirely resolved by the superimposition of entropy weighting. Also, the "quadratic" and "first two" maps are quite similar to their homologous for single piece batches, with the only notable exception that cases "qcet" and "qcte" for the "quadratic" law are not any more uncertain but clearly favour traditional mould making. Furthermore, focusing on the uncertain cases and considering the effect of entropy weighting, it can be observed that no rank reversals are introduced but, in the "quadratic" map, two cases that are in favour of conventional mould making become uncertain when entropy weighting is added.

Increasing further the size of batches to ten (Fig. 7), the most notable difference is the appearance of additional uncertain cases. Namely.

- in the "halving" weight distribution map, the case "qcet";
- in the "first two" weight distribution map the symmetric cases "cqet" and "qcet".

The "quadratic" law map shows again (like for the batches of five) two cases that become uncertain when entropy weighting is considered, although no rank reversals appear.

The most complex scenario is depicted by cases of the largest batch size considered in this study, i.e., fifty moulds per batch (Fig. 8). In particular, the "halving" weight distribution shows the highest and most intricate variety of results because the contribution of each category is never completely negligible (see Fig. 3) and, then, several uncertain cases emerge that are not simply attributable to one or two categories. The superimposition of entropy weighting does not help in making close results more clear and, on the contrary, a pair of significant rank reversals can be observed in the "cteq", "ctqe" and "qcte" cases. Although AM mould-making still appears the best alternative more frequently, conventional processes appear a better choice if cost and quality are very important. This principle is visible also in the "quadratic" map results where conventional mould-making appears preferable for about half of

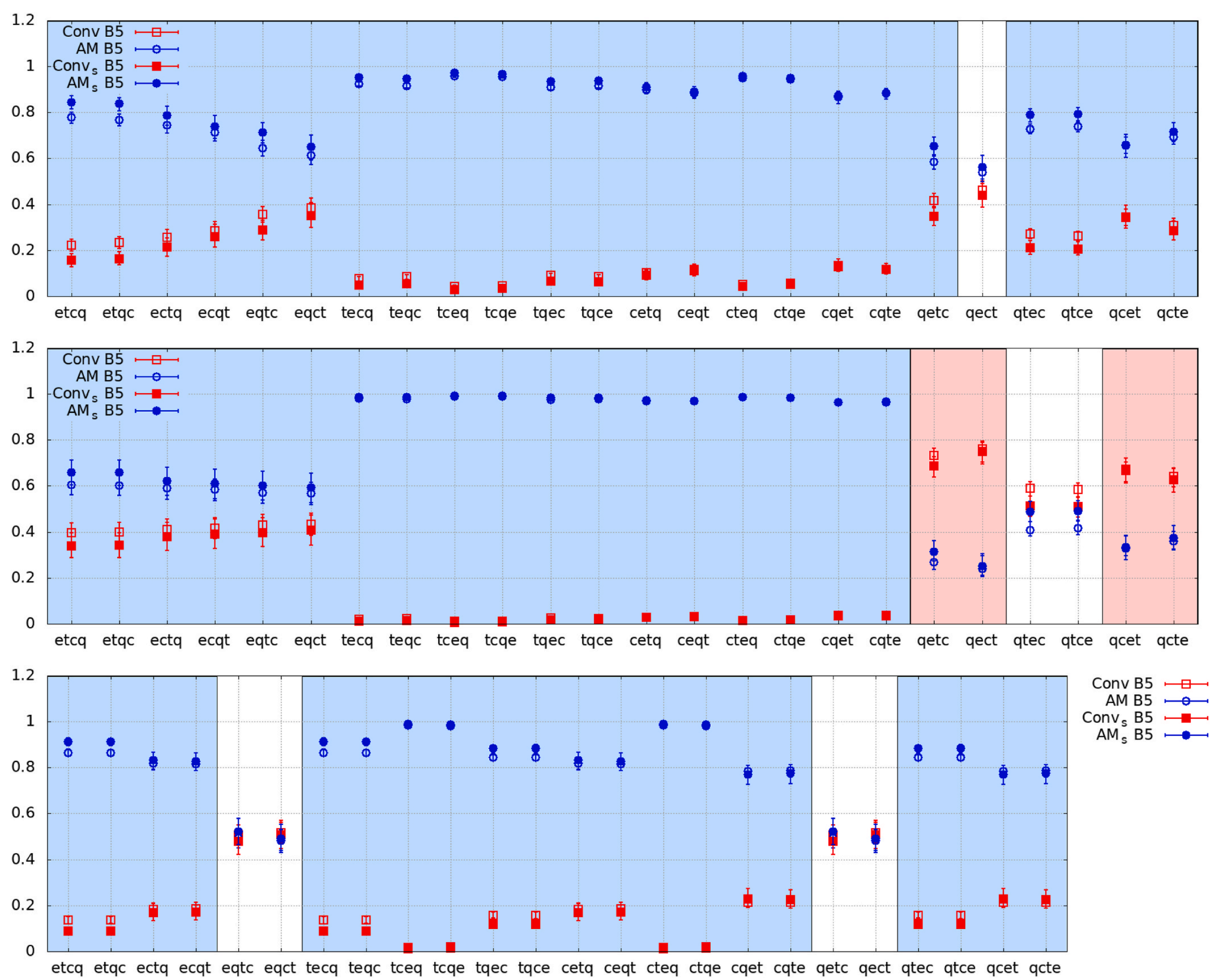

Fig. 6. Decision making maps showing the final score s^- of alternatives for batch sizes of five parts (B5) of the "halving" (top), "quadratic" (middle) and "first two" (bottom) weight distribution laws and 5% uncertainty of criteria values. The background colour indicates that the alternative with the corresponding data points is better, whereas no colour means uncertainty.

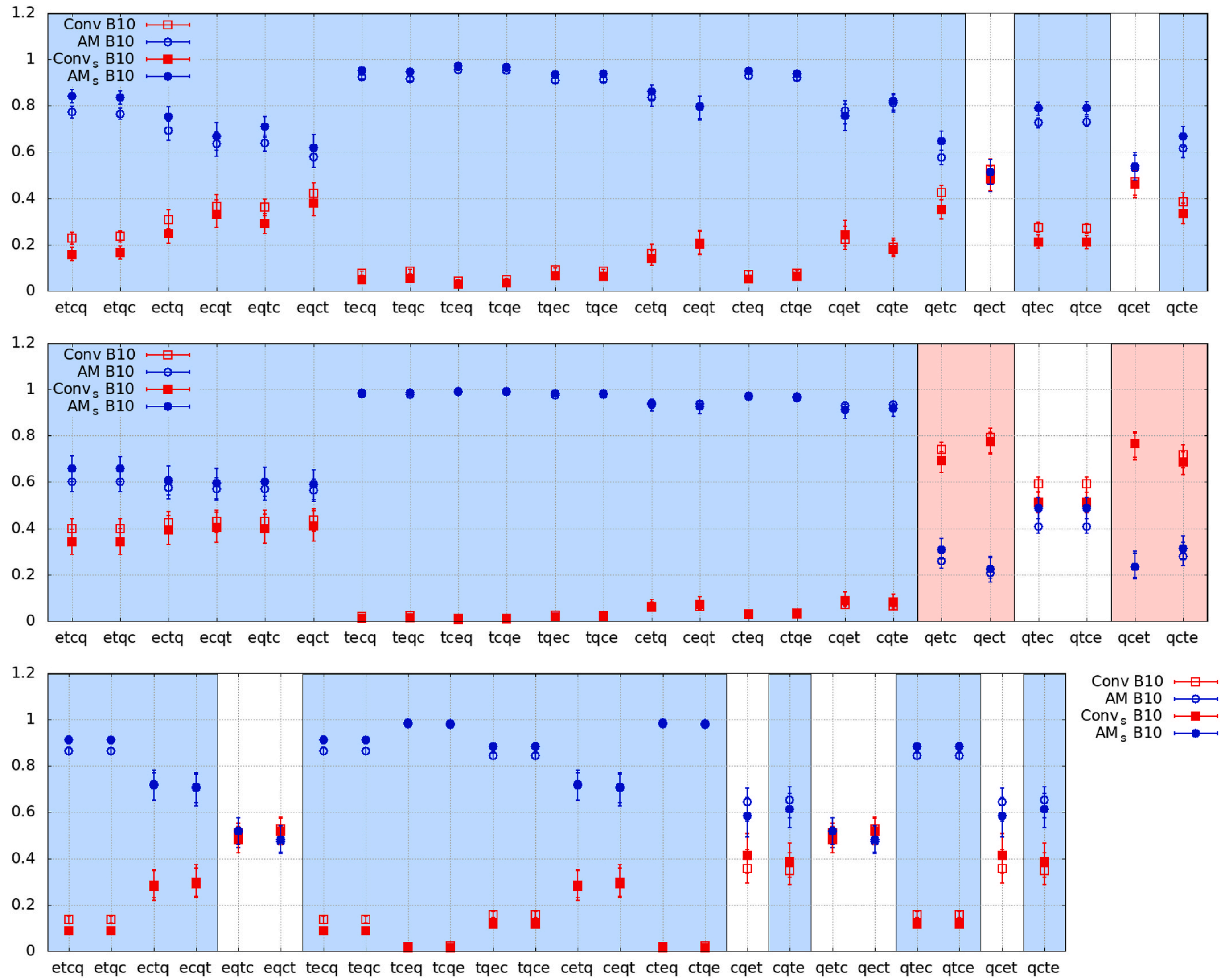

Fig. 7. Decision making maps showing the final score s^{-} of alternatives for batch sizes of ten parts (B10) of the "halving" (top), "quadratic" (middle) and "first two" (bottom) weight distribution laws and 5% uncertainty of criteria values. The background colour indicates that the alternative with the corresponding data points is better, whereas no colour means uncertainty.

the 24 cases. The uncertainty of cases "qtec" and "qtce" already observed for smaller batch sizes, is confirmed and, also in this case. Also the "first two" map repeats the four uncertain cases already seen for smaller batches (namely, "eqtc", "eqct", "qetc" and "qect") whereas the uncertain B10 "cqet" and "qcet" are for B50 clearly in favour of the conventional process. The results are found to be in accordance with the theories proposed by Almagharíz et al. (2016) on the economics of the AM based tooling techniques.

6. Conclusions

Metal casting is an energy-intensive manufacturing process for producing near-net-shape geometries. Capabilities of the traditional sand castings are often limited by the complexity of the intended shape to be produced. Additive manufacturing-based tooling, also known as rapid tooling, is a fast, economical and sustainable alternative for sand mould manufacturing. Binder Jetting is used for the 3D printing of sand moulds. This paper applies a robust decision-making framework to select the optimal process selection for sand mould production representing its decision-making maps. A multi-criteria decision-making algorithm named the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is linked to an automatic combinatorial method to produce high-resolution maps. Twelve indicators are categorised into four areas, environmental sustainability, quality, cost and time are established. Their impact on the overall mould manufacturing by conventional tooling and rapid tooling is computed, showing a complex decision-making space. The effect of the batch sizes, ranging from a single mould to a batch size of 5, 10 and 50 moulds, are examined. A 5% and 10% uncertainty in the values of criteria is considered for different batch sizes. Results indicate that for single mould production, the AM is the best option regardless of the specific weight distribution laws. However, on the contrary, conventional mould-making is more appealing to the decision-maker for larger batch sizes. Thus, the approach discussed in this work can be utilised to select an optimal mould manufacturing process based on the intended batch sizes to be produced.

7. Future work

The present approach can be expanded, and more deterministic criteria can be added to strengthen the discussed algorithm further. Hybrid manufacturing remains a challenge for the foundries. This work can be aligned with the concepts of Industry 4.0 and can be utilised to establish smart foundries. Furthermore, a real-life case study can be

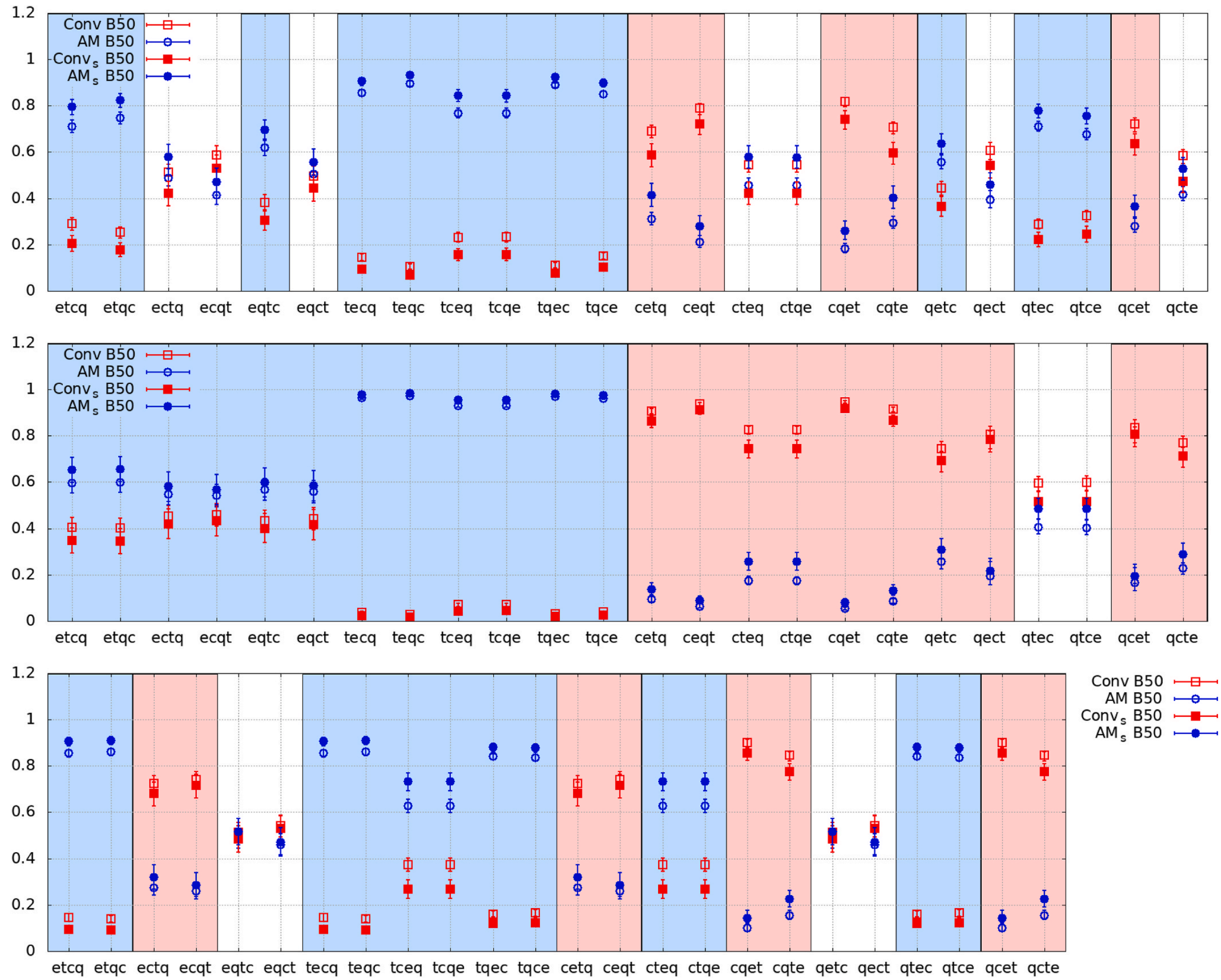

Fig. 8. Decision making maps showing the final score s^{-} of alternatives for batch sizes of fifty parts (B50) of the "halving" (top), "quadratic" (middle) and "first two" (bottom) weight distribution laws and 5% uncertainty of criteria values. The background colour indicates that the alternative with the corresponding data points is better, whereas no colour means uncertainty.

implemented, taking support from the discussed MCDM algorithm to develop advanced energy-efficient casting operations.

Data availability statement (DAS)

The authors confirm that the data supporting the findings of this study are available within the article.

CRediT authorship contribution statement

Prateek Saxena: Conceptualization, Formal analysis, Data curation, Validation, Writing – review & editing. **Emanuele Pagone:** Methodology, Software, Investigation, Formal analysis, Visualization, Writing – review & editing, Writing. **Konstantinos Salonitis:** Funding acquisition, Project administration, Writing – review & editing. **Mark R. Jolly:** Funding acquisition, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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